Finding the Optimal Trade Deal and Negotiating Target[1]

Eric Van Horenbeeck, *CNTS* University of Antwerp, EHSAL Brussels, December 2004

Abstract

Trade deals are an important marketing tool in many industries. They often have a direct impact on sales. In this paper it is demonstrated that the effect on sales is short lived and restricted between a lower and a higher response level. Both levels are governed by the long term customer franchise of the product, which is the result of a combination of several marketing parameters. Most marketing activities have diminishing returns and a method is presented to estimate the higher asymptote of such an S-shaped curve. A way to monitor the trade deal activities of a multi variety consumer product is presented as a case, although the method is not restricted to this field. The effect on sales of a trade deal may be temporary, following it on a longer time scale gives valuable insight on the health condition of a product or service in the market. In many companies however, the possibility of applying this monitor is hindered by accounting practices that do not register correctly or in sufficient detail the necessary input and output parameters.

Introduction and Background

Short-term trade deals are paid to the distribution by the manufacturer and are supposed to spur sales trough lower prices. The manufacturer expects the distribution to pass at least part of the deals to his clients. This allows the company to use the price variable of his marketing mix on a selective basis. A larger part of the price is often beyond control of the manufacturer: products do have ex-factory prices, but many companies rely on the services of a trade channel that is free to calculate and apply selling prices the way they feel apt (Dolan, 1995; Kumar et al., 2001). Companies record post factum how their products behaved in the field. Points in case are the supermarket and hypermarket chains. They control a dominating share of the retail grocery. The only way to support a product in a given region with a selected retailer is to influence the selling price with trade allowances on a short-term basis. As supermarkets work with limited warehouse capacity a price cut is the surest way to reach the consumer fast. It explains the wide spread use of this marketing instrument. A fair estimate of the amount of money spent, runs from 25% to 55% of the marketing budget for an average fast moving consumer goods manufacturer. According to the Wall Street Journal both Unilever and Colgate-Palmolive warned that 2004 profits would be lower because they need to spend more on promotional deals with retailers. Kraft Foods unveiled plans to spend up to an

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extra $600 million on in-store promotions this year. As a result, their spending on in-store promotions has grown, to 17.4% of sales last year from 14% in 1999, according to marketing consulting firm Cannondale Associates. That's on top of an additional 5% to 10% of revenue that consumer-goods companies have budgeted for traditional advertising. Such promotions can include price discounts to buy-one-get-one-free deals to hiring people to offer shoppers free samples of cheese or ice cream. Traditional supermarkets are asking manufacturers to shoulder more of the cost of these promotions as they try to lower their prices to compete with Wal-Mart Stores and Costco Wholesale. As a result, 51% of laundry detergents and 75% of carbonated beverages were sold on promotion last year in the U.S., according to Bain & Co (Ball, 2004). Attempts to break free from these restraints are almost impossible as even mighty Procter & Gamble learned. In 1991 the company launched its Every Day Low Prices (EDLP) strategy. The idea was to substitute nearly all short term promotions with advertising and lower consumer prices. The responses from consumers to P&G's shift to EDLP were unanticipated as was the impact on market share. Ailawadi, Lehmann, and Neslin (2001) discovered that market penetration from 1991 to 1996 was adversely affected by the EDLP strategy and was not offset through use of increased advertising.

This paper proposes a method to measure the short-term deals as a way to monitor the long term 'health' of products or services. The need to study the effect of promotional activity on consumer decisions has long been acknowledged (Gupta 1988; Chiang 1991). Decomposing the impact of price and promotion onto the effects on purchase incidence, brand choice, and purchase quantity allows manufacturers and the intermediary trade channel to better evaluate their promotional activities (brand switching versus purchase acceleration) and gives better insight into customer behavior. Research on these in-store decisions has focused on one of three parameters – purchase incidence, brand choice or volume bought (Neslin, Henderson and Quelch 1985; Krishnamurthi and Raj 1988, 1991) or analyzed them together (Gupta 1988; Chiang 1991; Chintagunta 1993). While these studies differ in many respects, those that allow the possibility that consumer decisions might depend on each other find support for this idea (e.g., the influence of the initial brand choice on the quantity to buy). Existing models for in-store decisions from the brand choice literature (Krishnamurthi and Raj 1988; Tellis 1988; Chiang 1991; Chintagunta 1993) all provide frameworks for the analysis of selectivity bias in those contexts and underline the importance of the short term effects on the competitive position of a product. Research by Simester (1995) indicates that consumers are aware of the marketing information for each product, but do not know how to use it until they visit a store. Experimental work by Alba et al. (1994) shows that consumers have quite accurate perceptions of differences in store-level marketing activity. In summary, research has identified dependence between the brand choice and purchase quantity decisions and the role of product pricing in these decisions.

Bounded Growth Models

The mathematical models used in this article are based on Ordinary Differential Equations (ODEs). Physicists first used ODE's to model the trajectories of moving objects. When applied to population or technologies they describe continuous paths of growth or decline through time. Although populations and many technological variables grow and decline in discrete numbers, continuous models are often used for simplicity when modeling large aggregates.

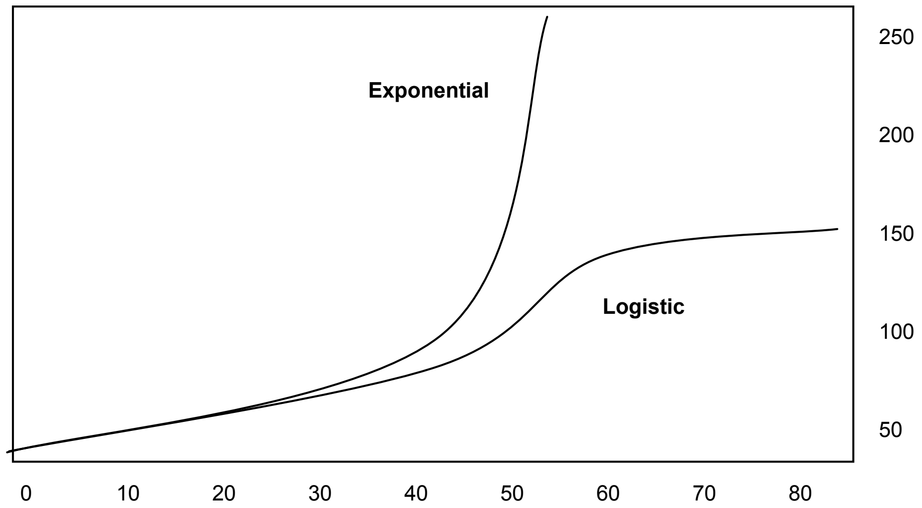

Figure 1

The exponential growth of multiplying organisms is represented by a simple and widely used model that increases without bounds or limits as Figure 1 illustrates. The growth rate of a population $P(t)$ is proportional to the population. The growth rate at time t is defined as the derivative $\frac{dP(t)}{dt}$.

The exponential growth model written as a differential equation

$$\frac{dP(t)}{dt} = \alpha P(t) \tag{1}$$

can be solved by introducing e (the base of the natural logarithm, approximately 2.71). A familiar solution to (1) is

$$P(t) = \beta e^{\alpha t} \tag{2}$$

where α is the growth rate constant and β is the initial population $P(0)$. α is often expressed as a percentage. An α with a value of 0.02, for instance, would be equivalent to the statement "the population grows continuously at 2% per period". Although many populations grow exponentially for a time, no bounded system can sustain exponential growth indefinitely. Because no real life systems are permanently unbounded and sustain exponential growth, equation (1) must be modified with a limit or a carrying capacity that gives it the more realistic sigmoidal shape of the lower curve in Figure 1. The most widely used modification of the exponential growth model is the logistic form. It was introduced by the Belgian mathematician Pierre Verhulst in 1838, but popularized in mathematical biology by Lotka in the 1920's, as Kingsland (1985) describes in her history of models in population ecology. The logistic equation begins with the $P(t)$ and α of the exponential method but adds the negative feedback term $\left(1-\frac{P(t)}{\kappa}\right)$ that slows the growth rate as the limit κ is approached:

$$\frac{dP(t)}{dt}=\alpha P(t)\left(1-\frac{P(t)}{\kappa}\right) \tag{3}$$

The feedback term is close to 1 when $P(t) << \kappa$ and approaches zero as $P(t) \rightarrow \kappa$. Thus, the growth rate begins exponentially but decreases to zero as the population $P(t)$ approaches the limit, producing an S-shaped (sigmoidal) trajectory. It is possible to solve the logistic differential equation (3) to find an algebraic solution. Often, more complicated differential equations do not have analytic solutions and must be simplified or solved numerically. The solution to the logistic equation (3) is:

$$P(t)=\frac{\kappa}{1+\exp(-\alpha(t-\beta))} \tag{4}$$

Equation (4) produces the familiar S-shaped curve. Three parameters are needed to fully specify the curve: α, β, and κ. The growth rate parameter α specifies the steepness of the sigmoidal curve. It is helpful to replace α with a variable that specifies the time required for the path to grow from 10% to 90% of the limit κ, a period which is called the characteristic duration or Δt. The characteristic duration is related to α by $\Delta t=\frac{\ln(81)}{\alpha}$ (Meyer, 1999). The parameter Δt is usually more useful than α for the analysis time-series data because the units are easier to appreciate. The parameter β specifies the time when the curve reaches $\frac{1}{2}\kappa$, the midpoint of the growth path. This parameter is the asymptotic limit that the growth curve approaches, also called the carrying capacity. The logistic model is symmetric around the midpoint. Other models exist that describe non-symmetric or skewed growth such as the Gompertz curve. Banks (1994) and Tsoularis (2001) review and compare several such models. See also Carillo & González (2002).

In Figure 1 both models have the same growth rate parameter α = 0:11 (approximately 11% per year) and a starting population of 1.22 at t = 0. For the first 20 periods the exponential and logistic curves are hardly distinguishable. After 50 marks the exponential curve has run off the chart while the logistic is stabilizing near the carrying capacity κ, in this case 150. The characteristic duration of this logistic, the time needed for the population to grow from 10% to 90% of κ, is 50, with a midpoint of 75.

A well-known marketing application of this approach was developed by Hanemann (1984). It showed that a model of joint discrete-continuous decisions, based on the actions of a utility-maximizing agent, can be derived as a special case of a more general statistical model of switching regressions. This framework has been applied in the marketing literature in the domain of category level decision-making (Chiang 1991; Chintagunta 1993). Unfortunately, the approach is not directly applicable when one considers a sequential discrete-continuous decision in which information available to the decision-maker changes across the two decisions. In Hanemann (1984) the decision-maker must have all the relevant information available to decide on the brand selection and the purchase quantity from the start of the process. Any new and relevant information for one of the decisions cannot be uncovered from the outcome of the other. When modeling brand selection and purchase quantity decisions it is reasonable to assume that all the prices for each alternative, and all the remaining relevant information for the decision process, is either known or available costless by simple in-store inspection. In addition the customer will be faced with an overall store environment that will influence his expenditure decision and that is not known before visiting the outlet. To be sure, consumers may build expectations of prices (using previous price levels), availability, and general store environment, and use these expectations together with other variables (e.g. distance to store) to choose which store to visit. But once a store is chosen and visited, the consumer will acquire new information relevant to the expenditure decision. Hanemann's approach also imposes severe restrictions on the elasticity structure and the functional form of the expenditure equation (Chintagunta 1993).

The Logistic Model

Another acknowledged model in this field is the Fisher and Pry Transform. Fisher and Pry (1971) have successfully exploited the logistic model to describe the market penetration of many new products and technologies. Usually we first visualize logistic growth by simply plotting data on an absolute and linear scale. A change of variables that normalizes a logistic curve renders it a straight line. This view is known as the Fisher and Pry Transform:

$$FP(t) = \left(\frac{F(t)}{1 - F(t)} \right), \text{where } F(t) = \frac{N(t)}{\kappa} \tag{5}$$

and:

$$\ln(FP(t)) = \frac{\ln(81)}{\Delta t}\left(t - t_m\right) \tag{6}$$

So if $FP(t)$ is plotted on a semi-logarithmic scale, the S-shaped logistic is rendered linear. Problem is that one still needs to estimate the rate constants. Furthermore the assumption that a novel product will eventually replace 100% of an existing application is a very strong simplification. It takes for granted a one to one mapping from the user requirements covered by the novelty onto the needs addressed by the previous solution. An innovative item can replace more than one existing product or service and often adds a few conveniences that are completely new to the world on top of that. The same line of thought holds for promotional stimuli: it is difficult to maintain that one unit bought at a promotional price, replaces one unit of the same product at the standard price. Lower prices have a marked positive effect on products with a high basic customer franchise but generate little or no response on less popular goods whatever the price cut (Garretson and Burton, 2003). Lowering the price does not change the value to a customer. Several other S-shaped curves are described in textbooks, but real life applications in the marketing field are hard to come by. The main reason seems to be the assumption that a good guess for the asymptote is available in order to solve the equation. But this upper limit is precisely what we are looking for! A second problem is the variance of the data, more specifically the heteroscedasticity due to asymmetric X and Y values.

P. Young evaluated nine different growth curve models, using a collection of 46 data sets representative of growth behavior encountered by technological forecasters (Young, 1993). In each data set, the last three data points were held out to be compared with the forecasts based on the earlier data points. Two findings come out of the research:

- Models giving the best fit to the historical data as measured by mean square error were in general not very good in forecasting. Obviously, a forecasting model should fit future data. Getting a model that matches the process is more important than getting a good fit to the historical data.
- If the upper limit is not known, neither the logistic nor the Gompertz, nor any of their variants performs very well. Attempting to extract the upper limit from data early in the growth curve is not a good idea.

Avoiding κ

Based on research reviewed in the introduction and on empirical data, we may rename the asymptotes of an S-curve in the marketing domain the Lower and Upper Response Level. This relabeling underlines the fact that in the short run sales without external stimuli will not disappear altogether but will land on a level well above zero and defined by the basic customer franchise of that specific product. On the other hand the sales expansion is also bounded in the short run: unlimited stimuli will not generate unlimited sales, giving away the product for free does not generate infinite demand. Because the observed data do not follow a straight line between those two levels regression techniques are necessary to find the most suitable mathematical model. The standard logistic model and its S-curved relatives need three parameters: α, β and κ. The first two are deductible from the data, κ is exogenous. How can we avoid the use of this factor? The stimulus-response relation of prices and volumes is based on the expectation and the observation of a change in some quantity Y as a result of a change in some quantity X, bounded by an unknown factor κ. Data *inside* the bounded region should have a statistically normal distribution. Data *outside* the bounded region are likely to behave significantly different. The error function *erf*(x), also called the Gaussian probability integral (Harris and Stocker, 1998), is the area under the curve between the variable limits $-x\sqrt{2}$ and $+x\sqrt{2}$:

$$erf(x) = \frac{1}{\sqrt{2\pi}} \int_{-x\sqrt{2}}^{+x\sqrt{2}} e^{-y^2/2} dy = \frac{2}{\sqrt{2\pi}} \int_{0}^{x\sqrt{2}} e^{-y^2/2} dy \qquad (7)$$

$$erf(x) = \frac{2}{\sqrt{\pi}} e^{-y^2} \sum_{n=0}^{\infty} \frac{2^n y^{2n+1}}{1 \cdot 3 \cdot \ldots \cdot (2n+1)} \qquad (8)$$

This is the area where one would expect to find the data that respond appropriately to a stimulus.

To implement an approach that discriminates between normally distributed data and the other, one needs an iterative function. If a particular term added to the previous data does not change the result by more than a given tolerance, we have the probability that the new observation falls within s standard deviations of the mean, assuming a normal distribution. If it falls outside the probability area we conclude that the given stimulus no longer produces an acceptable response. Figure 2 is based on a similar observation made by Theodore Modis and Alain Debecker (Modis & Debecker, 1992)

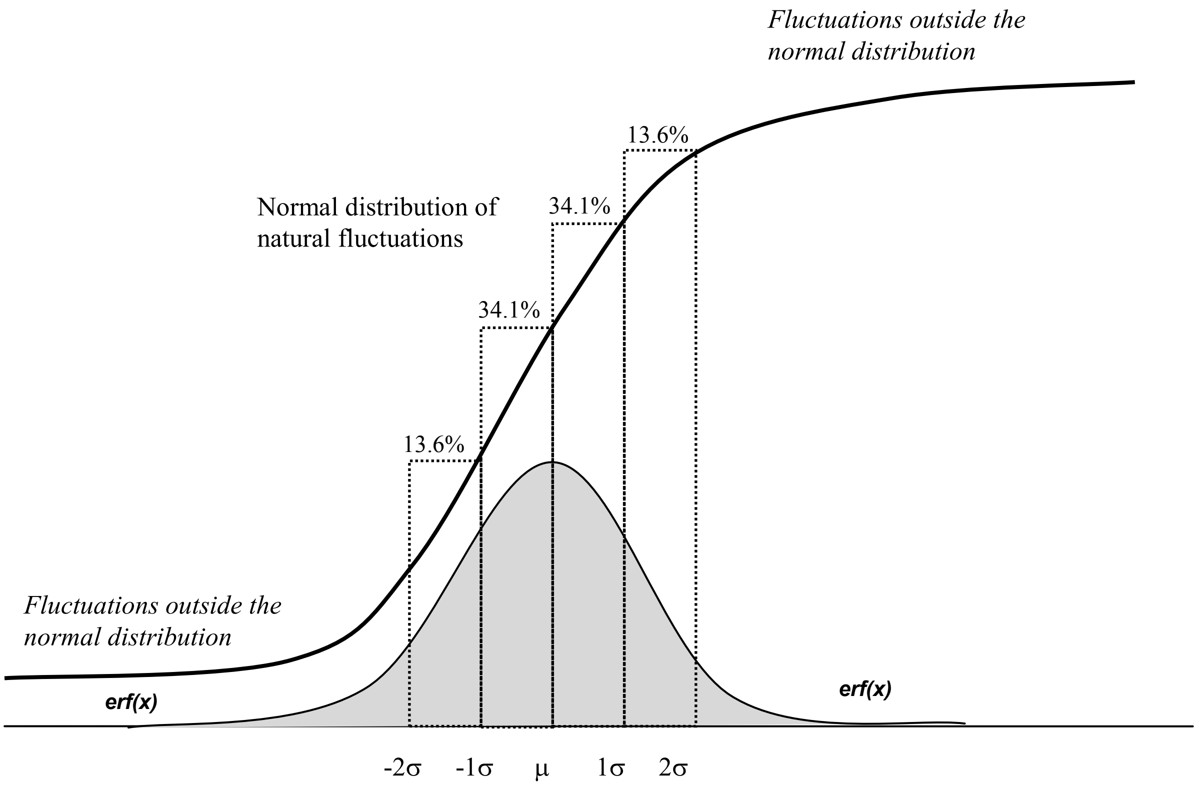

Figure 2

Figure 3 shows an idealized representation of the different elements of this approach.

- The S-curve traces the hypothetical path from the Lower to the Upper Response Level.
- The regression line can be understood as the cumulative mean value for *Y* and the corresponding value of *X* building up from left to right for sorted values of *X*.
- A perfect symmetric distribution of the observed data around each point on the regression line higher than $\bar{X}$ yields a value of 0: this is the intersection of the S-shaped line with the regression line.
- The geometric mean of the remaining observations calculated to give the Upper Response Level.
- This approximation is a momentary point in a discrete set of data; no extrapolations should be made outside the range of observations.
- New data can be added at each period.

A feature of this set-up is that it offers an approximation of the 'ceiling' or higher asymptote. The proposed model could be described as adaptive and iterative, because its parameters are updated periodically on basis of new information and because the data are assessed by an iterative routine, rather than by evaluation of the full data set at once.

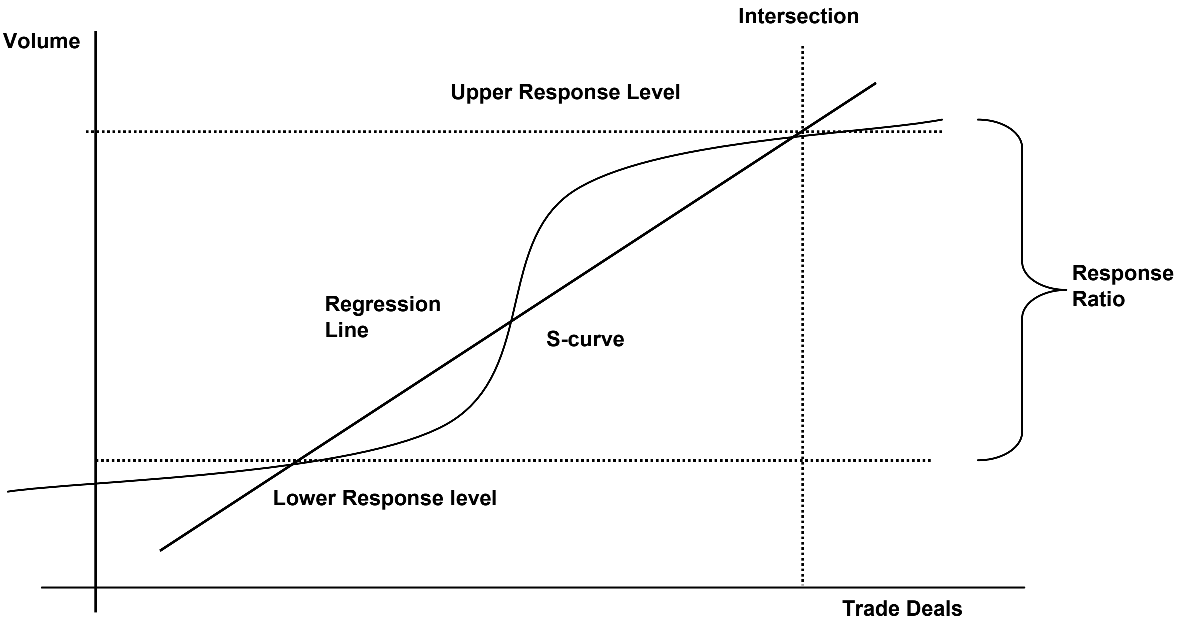

Figure 3

Monitoring Trade Deals

In order to test the application in real life circumstances, we consider a food company that markets a product line with many varieties[2]. The products are grouped in 5 price brackets. This consumer brand is a leader in its segment and enjoys a broad distribution. In a regional market of 4 million households, the company sells 25 million units a year. The company has a trade-dealing budget of 5 million Euros, about 25% of the total marketing budget that includes above-the-line advertising, marketing research, consumer promotions, and sponsoring. The company has a general impression that indiscriminate promotional dealing with a lot of varieties together does not pay off maximally in terms of volume sold and that it brings down the product profitability. The product line itself is fairly profitable in general. In the short run no major technological breakthrough is to be expected and a strict cost efficiency program is needed to maintain profitability and market share.

Stiff competition, pressure on the prices by retailers and possible substitution by other product categories limit the possibility of passing on easily the inflationary rising cost of goods. All this urged management to take a closer look at the promotion policy. A first reaction was to restrict the number of promotions with those varieties that were more expensive to produce. The sales force feared this would lead to loosing goodwill with the trade and lower overall sales to the consumer. The measure would increase paperwork and warehouse handling costs. Guiding more precisely how trade customers for a promotion have been selected, did not lead to any savings either because there was no way to implement and to control the selection criteria.

[2] Real figures from a non-disclosed American Food Company in Europe

Is it possible to set and evaluate Trade Dealing Targets?

Against this background the question was raised: why do we need promotional outlays in the first place and what do we get in return? Prior to any analysis relevant data are needed. For every month and for every variety the volumes sold were put against the different trade deals and free goods (expressed as a percentage of gross sales). These deals vary over a large range, mainly because the number of customers participating. The deals itself are quite straightforward: 10% off the standard price, a '*Buy 10, Get 1 Free'* offer, or any other similar promotional scheme.

Both fast selling and slow selling varieties showed to correlate highly with the trade deal level. The correlation (r^2) between the volume of the 11 best selling varieties and the corresponding trade deal level is 0.70. These varieties do 70% of the volume sold and use 83% of the trade deals spent. (Figure 4)

Figure 4

Important however, is the fact that this correlation not linear, but S-shaped. Every variety appears to have its own lower response level. The Lower Response Level is the amount of product sold at a trade level of 0 %. At that point sales are defined by:

- Distribution ratio
- Customer acceptance of the generic product
- Functional product satisfaction
- Brand loyalty

In other words, sales are defined at that point by the Basic Customer Franchise, given a constant level of distribution, competitive pressure, and advertising exposure. The Lower Response Level is a long-term effect of a series of marketing variables. From the zero level onwards sales show increasing marginal returns, and then a diminishing return with respect to the various alternate levels of deals. The demand curve might suggest a continuum, but it is not as was demonstrated earlier in this paper. The proper interpretation of what we see is a discrete set of trade deals levels and its associated sales response per time period.

At a certain point the Upper Response Level is reached. The same Basic Customer Franchise ruling the Lower Response Level now marks the upper limit: whatever the deal, from a given point on the market will take no more. Between those two limits lies the Response Ratio of each variety, and in general of every product. The part of the graph between the Lower and the Upper Response Level has an elasticity of $-1 < e <= 1$.

One point more deals may result in:

- A proportionally higher volume sold;
- An extra volume rising at the same speed as the deal;
- A proportionally lower volume, when deals outlays grow faster than the resulting sales.

When looking at the average sales and trade deals of the 11 best selling varieties we observe $e \cong 0.5$ In order to sell 50% more one has to give 100% more deals. However, these aggregate figures mask great differences: a top seller in the group has an elasticity of 1. A slow seller has an elasticity of almost 0: no matter how high the deals, the volume sold remains static. Based on these observations optimizing the use of dealing money as a true incentive could go along the following steps:

1. Define for every product the optimal trade deal rate (as a percentage to gross sales). This point lies at the Upper Response Level of the curve.
2. Define the Lower Response Level.
3. Define the volume necessary and sufficient to reach sales target.
4. Define selection of trade partners to deal with.
5. Set negotiating targets.

The Promotional Model

In this particular case we consider as given the yearly volume of the product range and the proportion of each variety therein. The promotional volume of a variety is a short-term sales increase needed to reach the sales target of that variety.

1. Define the volume to be sold as a promotion.

The Lower Response Level indicates the volume sold without extra incentive, thus the promotional volume is:

$$QP = QT - QLy \qquad (1)$$

Where: QP is the promotional volume

QT is the target volume (total sales to be reached in a given fiscal year)

QLy is the lower response level on a yearly basis

2. Define the number of promotions necessary and sufficient to reach the sales target

$$Pn = \frac{Qp}{QUm - QLm} \qquad (2)$$

Where: Pn is the number of promotions

QUm *is* the upper response level (the local maximum sales response to deals) on a monthly basis

QLm is the lower response level on a monthly basis

$$QPt = \frac{QP}{Pn} \qquad (1)/(2)$$

Where: QPt is the average promotion volume in period t

3. Draw a list of customers participating in promotion Pt

This can be done by running over the customer file and selecting candidates on a limited set of criteria:

- Is the product introduced in the customers’ distribution system?
- Did the customer have a promotion on the same product in previous period?
- Does this customer relate to other selection criteria, e.g. shop type, region...

Customers are selected until their combined estimated sales volume equals the promotional sales target.

4. Calculating the Upper and Lower Response Levels

Let's take a look at two products: the top selling Product A and the less popular Product B. In the course of a year the following trade deals were given, resulting in the corresponding sales volumes:

Trade Deals (% to gross sales)		Sales Volume (x ‘000 units)	
A	B	A	B
1.9	2.5	227	38
3.6	3.1	257	30
3.7	3.3	235	42
4.2	3.4	278	30
4.6	3.9	287	29
4.7	4.3	300	44
5.2	4.5	263	39
*5.3	*4.5	320	51
5.4	4.5	293	48
5.7	5.0	453	70
5.9	5.7	340	39
6.1	6.0	258	50
4.7	4.1	3,511	510
Average deal		Total volume	

* Intersection point

Table 1

In this case the best fit is obtained with a bivariate exponential regression function for product A and with a bivariate power function for B. A significant correlation of 0.63 is obtained for product A. The correlation for B is a low but still significant 0.53.

When no significant correlation between deals and volume can be found, the conclusion would be to stop all promotion at once. A severe cut in the promotional outlays for product B is suggested and is possible without a noteworthy loss of the volume sold as will be demonstrated hereafter.

The Lower Response Level is defined as the volume at trade deals = 0%. It is the intersection of the regression line with the y-axis with the general form:

$$b = \frac{\sum y - m \sum x}{N}$$

Where: m = the slope of the regression line

N = the number of observations

The value for product A = 182,000 and for product B = 20,200 (monthly avarage)

The crossing between the S-curve and the regression line took place at 5.3% and 4.5% respectively, and the geometric mean of the remaining values yields an upper limit of 327,000 units for product A and of 50,000 units for product B (monthly average).

The most appropriate trade deal stimulus for product A is 5.3% and 4.5% for B. Other deals are either too low (sales volume missed) or too high (trade dealing money wasted).

5. Filling in the Figures

Suppose a yearly sales target of 3,511,00 units for the popular A (Figure 6 below) and a target of 510,000 units for the slower selling product B (Figure 7) how many promotions do we need to reach these targets and at what cost?

- Promotional volume

$QP = QT - QLy$ (1) Where: QP is the promotional volume

QT is the sales target

$3,511 - 2,184 = 1,327$ (A) QLy is the yearly lower response level

$510 - 242 = 268$ (B)

- Number of promotions

$$Pn = \frac{QP}{QUm - QLm} \quad (2)$$

Where: Pn is the number of promotions per year

QUm is the monthly upper response level

$\frac{1,327}{327-182} = 9.1$ (A) QLm is the monthly lower response level

$\frac{268}{50.3-20.2} = 8.9$ (B)

- Trade Deal Level

For the same volume the average monthly trade deal level was 4.7% for A and 4.1% for B (see table), or over the whole year:

12 x 4.7 = 56.3 (A)

12 x 4.15 = 49.3 (B)

A necessary and sufficient dealing package could be:

9.1 x 5.3 = 48.6 (A)

8.9 x 4.5 = 40.1 (B)

Applying this second dealing scheme would amount in savings of 14% on the budget for variety A and of almost 20% for variety B for the same volume sold.

One should not underestimate the leverage and payoff of improved pricing. Compare, for example, the profit implications of a 1% increase in volume and a 1% increase in price. For a company with average economics, improving unit volume by 1% yields a 3.3% increase in operating profit, assuming no decrease in price.

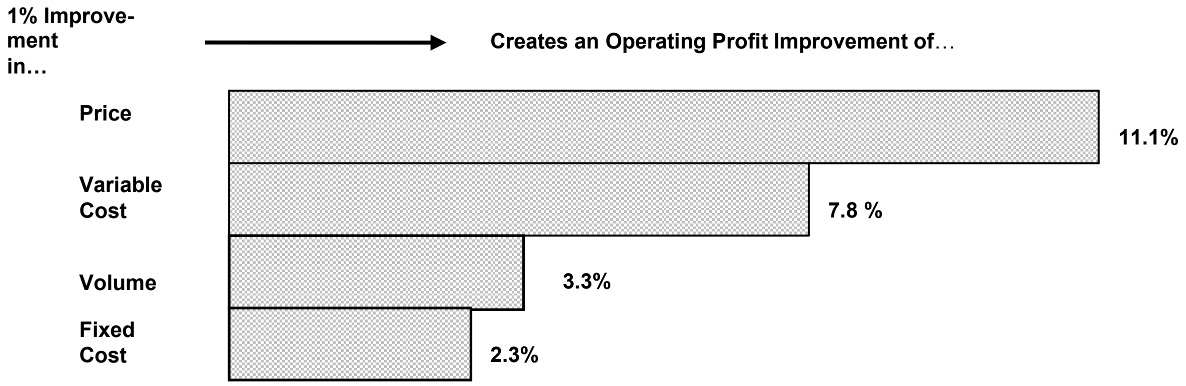

Figure 5 **Profit Leverage**

But, as figure 5 shows, a 1% improvement in price, assuming no loss of volume, increases the operating profit by 11.1%. Improvements in price typically have three to four times the effect on profitability as proportionate increases in volume. Figure based on average economics of 2,463 companies as published by Marn and Rosiello (1992).

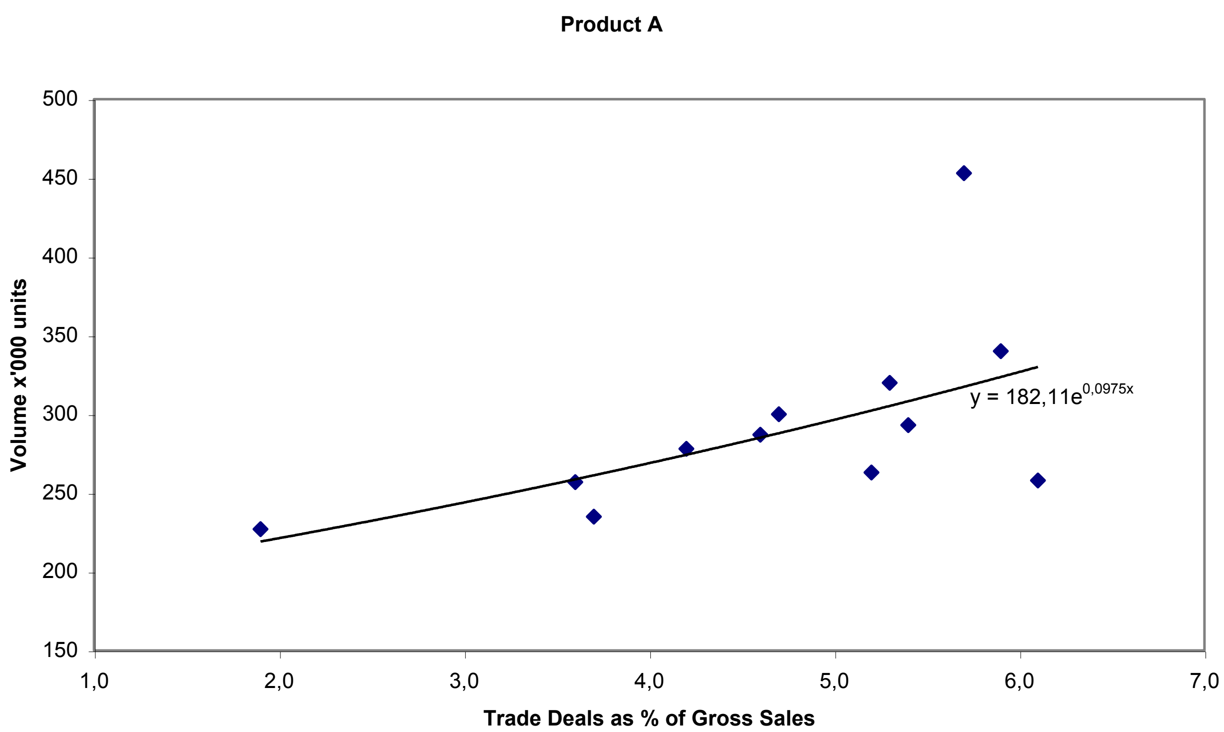

Figure 6

6. Setting negotiating targets

Suppose we selected a list of customers that will be offered an extra price-off in exchange for a fair order. It's then up to the account negotiator to get the most out of it, in other words his objective is to sell more. 'More' means that the *promotional* order of the average customer should increase with the same ratio against a *normal* order as the ratio between the Lower and the Upper Response Level for that product:

Negotiating target = $\frac{QU}{QL}$ Where: QU is the upper response level

QL is the lower response level

The negotiating target for product A and B:

$\frac{327}{182} = 1.8$ (A) $\frac{50.3}{20.2} = 2.5$ (B)

In words: a promotional offer for product A should yield on average a volume that is 1.8 higher than what one would expect from an order at standard prices and that is 2.5 times higher for product B.

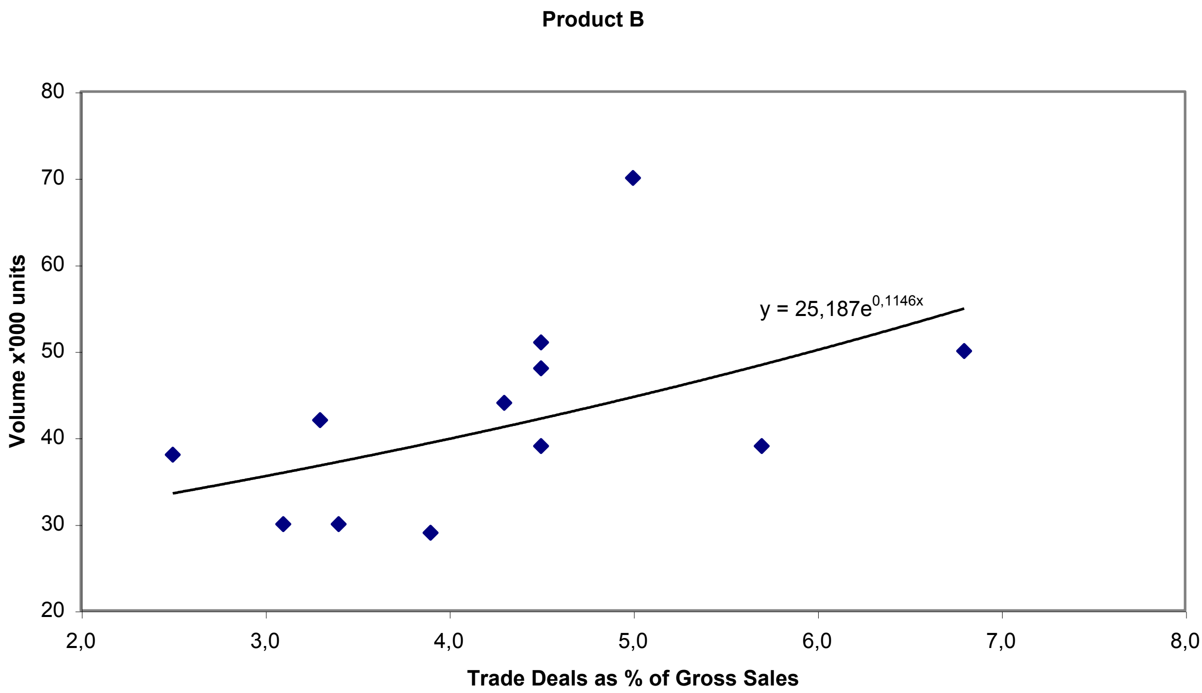

Figure 7

Two final remarks concerning the trade dealing practice:

- The improved dealing proposition for product A is: 9.1 times 5.3%. But what if some promotional activity is needed for every month of the year (instead of for 9.1 periods)?
- Trade deals offers tend to be in a standard format: e.g. a 10% rebate on invoice, or 10 + 1 in free goods; how then could a 5.3% deal be offered to the distribution?

The purpose of this model is to approximate the optimal stimulus needed to reach a given sales target. As long as the total input remains the same, we can write the terms differently to suit a particular timing, customer selection, and formulation of the deal. In the case of product A this stimulus can be formulated as follows:

(1) Discount rate %	(2) Participating clients. 1 = 100%	(3) Promotion periods	(4) Total Deals (1 x 2 x 3)
5.3	1.00	9.1	48.2
4.0	1.00	12.0	48.0
10.0	0.40	12.0	48.0
10.0	1.00	4.8	48.0

Table 2

The first line in the table gives the optimal promotional mix as calculated with the discount rate in the first column (1) then the rate of the participating customers (2), the number of promotional periods (3) and in the fourth column the total deals indicator, being the product of the first three columns. The second line in the table proposes a promotion of 4% on gross sales every month to all customers, what would amount in the same outlay with the same resulting sales volume as in the first line. The third possibility is a 10% rebate every month but offered only to a selection of customers, doing 40% of the sales of that product. Finally, it is possible to offer a 10% deal to all customers, but only 5 times (4.8) a year.

The Long Term Value of Short Term Actions

Decisions that are made regularly tend to become routine especially when it is hard to see how to correct or improve them.

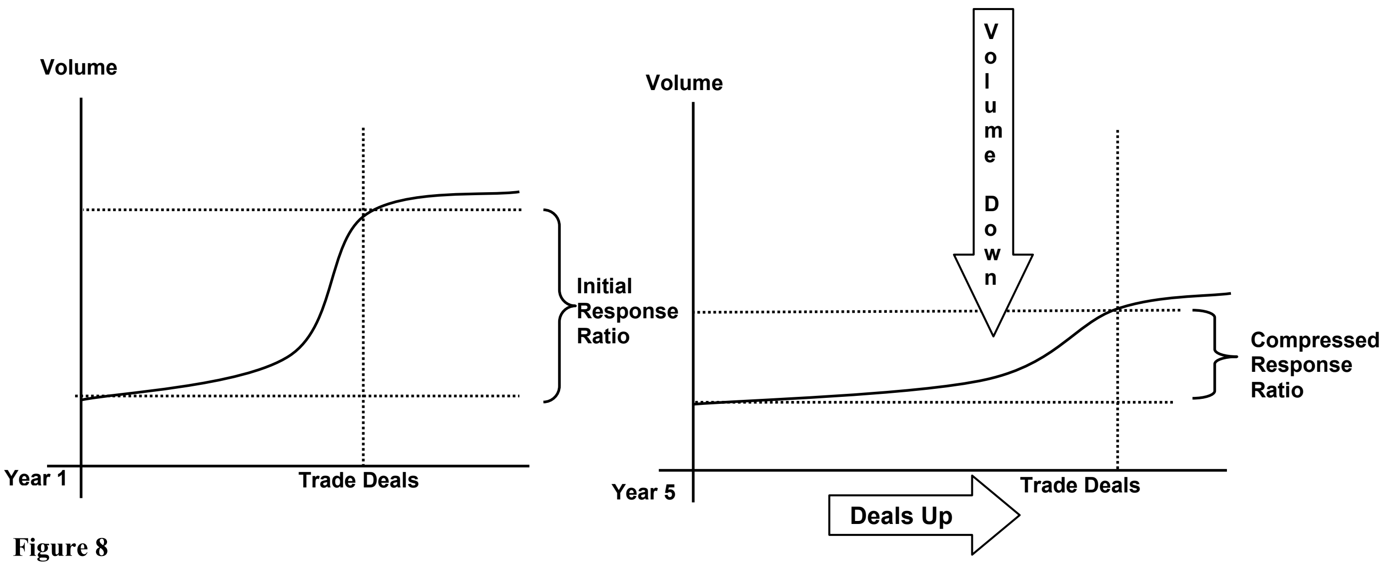

Figure 8

In one company a diminishing Upper Response Level has been observed over a five year period despite increasing average trade deal rates from 4.8% to 8.5% on sales (Figure 8).
Monitoring the promotional outlays and the sales effects triggered by them helps management to improve control over the product contribution. It also assists the sales force in setting negotiating targets with selected customers. Over time a shift in the Basic Customer Franchise, as expressed in the response ratio between Lower and Upper Response Levels can be measured. An early warning can be given when products fail to respond to direct stimuli or when permanent price cuts are necessary to reach sales targets. Other instruments could be brought in action or it might be worthwhile to consider withdrawing the product from the market.

Price Wars: the Competitive Perspective

Trade deals and price cuts are of course not only probes to test the market acceptance of a product or service, they are first of all weapons used in a competitive battle. A company may not be able to explore the full path between the Lower and Upper Response Level because the S-curve of its product ends in discontinuity. Discontinuities occur when the costs of the attacking business become equal to, and less than, the costs of the defending business. These costs are in fact the aggregation of two different costs. The first is the *full cost* necessary to reach the target levels of return, for example a 15% return on invested capital. Full cost includes all the cash costs for supporting the business (including the costs of developing, making, selling, distributing, and servicing the product) as well as depreciation of capital equipment, amortization of goodwill, and profit for the bond and equity holders. The second cost is the *cash cost*. This is the 'rock-bottom' cost needed to avoid losing cash. Cash costs are always less than the full costs. They do not include depreciation and profit for the equity holders. The difference between the cash costs and the full costs is the *margin*. These costs are generally declining for both the attacker and the defender, but they are falling faster for attackers, who are earlier in the evolution of their business than are the defenders.
On the other hand, the assailant's costs are generally higher in the beginning than the defenders, since the attacker is just getting started. The result is a crossover point, the point where the attacker's cost becomes equal to, and then less than, the defender's cost. Since the attackers and defenders are both concerned with cash and full costs, there are actually four points of intersection, as shown in Figure 9:

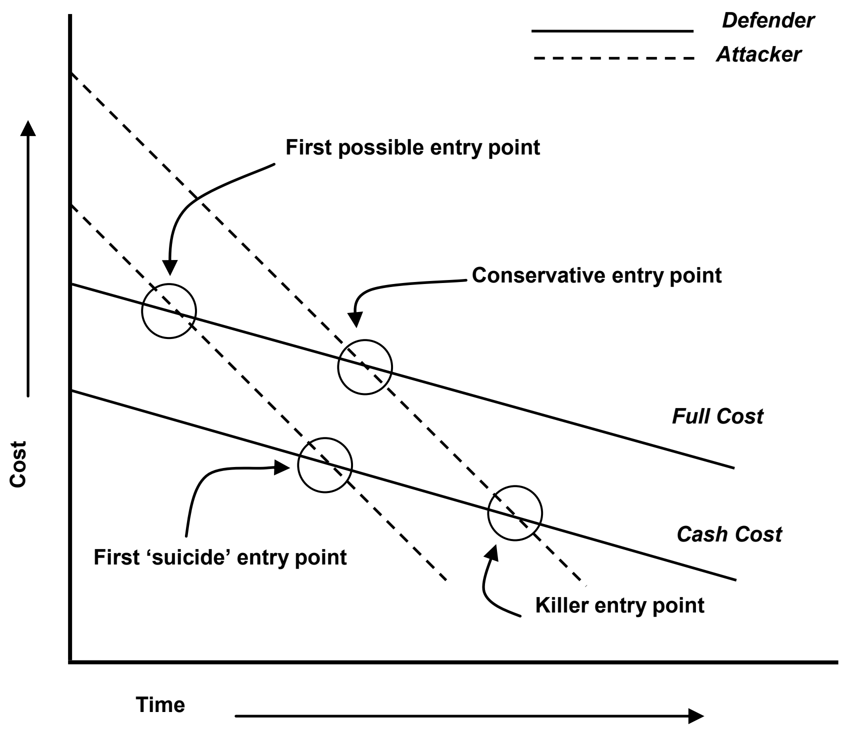

Figure 9

The simplest point to understand is the conservative entry point. This is the point where the full cost for the defender and the attacker are equal. At this point, if the defender wants to defend, it can do so by cutting prices and thus cut into its margins. To meet this defence, the attacker will have to reciprocate by cutting prices and cutting into its margins. The ultimate winner is the competitor with the lowest cash costs. The earliest point at which it makes economic sense to attack is when the cash costs of the attacker are equal to the full costs of the defender. The assailant may be willing to sacrifice all profit margin but will not be losing out-of-pocket cash as long as the defender does not react, which is highly unlikely. The defender is much more likely to retaliate by cutting prices without risking negative cash flows, thus bringing real economic harm, and perhaps death, to the attacker. There are few successful attacks at this point, but many are attempted nevertheless.

For the conservative attacker, waiting until his full costs are less than the cash costs of the defender is a safe strategy. There is one other significant point at which an attacker can attack, and that is where the cash costs of the attacker are equal to the cash costs of the defender. The full cost of the attacker at this point is usually no less than the full cost of the defender. Often it is more. But the attacker, if it is willing to not recover its full cost, can compete at the defender’s price. The defender’s main weapon, reducing price to its cash costs in order to bleed the attacker, cannot work at this point, because the attacker has the same cash costs as the defender. The deep-pockets defence is still applicable here, since the defender can subsidize its cash costs from another division or from the company's retained profits. The defender will bear real pain here, and thus may be less likely to be as aggressive. There is still plenty of risk and exposure for the assailant but less so than at the first point of attack. To the customer's benefit, prices will have fallen substantially by an amount roughly equal to the defender's original margin plus the value of the relative productivity gains over the length of the discontinuity. It can be a meaningful amount: often 25% or more of the price at the beginning of the discontinuity. Empirical market evidence suggests that the transformation of market share occurs in parallel with the process of price change (Foster and Kaplan, 2001). Monitoring the Response Ratio will help management to assess the viability of its product under attack.

Getting to the Right Figures

Putting promotional costs under the microscope is important. Companies adopt widely differing practices in accounting for them. They have a large element of discretion on how they treat and disclose these costs. The use of free goods and cross-promotions have been rampant in many businesses not only in the food sector. Companies often tag on a free tube of toothpaste with a bar of soap or offer three packets of coffee for the price of two. How are these free samples captured in a company's accounts? Quite a few companies add the cost of production of the free samples to the advertising expenditure and total up the expense simply as advertising and promotional expenditure with no break-up of expenses between the two categories. Others delineate advertising and promotional expenses separately on the expenses side of the profit statement. But yet others include the cost of raw materials, wages and manufacturing expenses incurred on free samples under the respective heads of accounts.

		Estimated Real Gross Profit (GP)		Actually Booked GP		Variance	
x'000$	Net Sales	GP %	GP $	GP %	GP $	Estimated vs. Actual	As a % on Sales
A	1,216	45.8	557	16.9	206	351	28.9
B	3,855	25.7	991	11.0	423	568	14.7
C	2,807	40.1	1,126	20.6	577	549	19.7
Total	7,878	33.9	2,674	15.3	1,206	1,468	18.6

Table 3

In a small survey of 25 companies, only 5 where able to produce accounting data in sufficient detail allowing the calculation of a response ratio as described in this paper. In one extreme case a company reported a decrease in overall Gross Profit from 30% on Net Sales to 22% over a three year period. After analysis of the figures it turned out that the company booked free goods and samples simply as sales with a value of zero and not as a separate promotional cost. Possibly this is a tolerable accounting practice, but it completely blinds the management. See Table 3 for an example with three products. Similar findings were reported by McKinsey (Marn and Rosiello, 1992). They found, for example, payment terms discounts buried in interest expense accounts, cooperative advertising mixed with companywide promotions, and advertising line items, and customer-specific freight costs that were lumped in with all the other business transportation expenses.

Conclusions

A lot of processes in business react to a stimulus with diminishing force. Knowing beforehand the ceiling one is going to hit has many practical implications. Monitoring the effects of price changes is important in the short run and it offers insight in the long term health condition of a product or service. However, the existing equations are not easy to implement and to use as a method for day-to-day management. An interesting method is to sidestep the need to the estimate κ; the carrying capacity, or asymptote of an S-curve. It can be done by disaggregating the data in two sets: a normally behaving set and a set outside the Gaussian distribution. The proposed model is not a continuous function but an estimator of two discrete points: a lower and an upper level.

Strangely enough few companies have the necessary data readily available. Not only the impact on operating profit of ill allocated cash resources is underestimated, they fail to see the marketing possibilities of target setting and the strategic importance of the information gained from long term deal monitoring. Implementing this or similar schemes in these companies is not feasible without preliminary work on the way the promotional outlays are registered in their accounting systems.

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